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Optimized Logistic Routing Based On The Travelling Salesman Problem: Cost Reduction And Operational Efficiency In A Regional Distribution Network

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Abstract:
Background*: Distribution logistics plays a fundamental role in the competitiveness of companies, especially in regional contexts where transport infrastructure and the geographical dispersion of clients impose significant challenges. In the state of Espírito Santo, the absence of applied studies that explore logistic routing with a focus on cost reduction and increased operational efficiency highlights a critical gap both in the academic literature and in management practices. This study is justified by the need to optimize the regional distribution network, supporting strategic transport decisions in organizations operating with multiple service points and specific operational constraints.*
Materials and Methods*: The research adopts a quantitative approach, with a design based on a case study applied to a wholesale company in the state of Espírito Santo. Secondary data were used, referring to routes, delivery volumes, travel time, and the geographical location of clients. Data collection was supported by operational records and digital route mapping. The modeling was carried out based on route optimization algorithms, considering variables such as distance traveled, service time, and vehicle capacity. Tools such as Google Maps were employed in the simulation and evaluation of alternative routing scenarios.*
Results*: The results indicated a potential reduction of up to 18% in total travel time and 22% in operational costs through the application of the proposed routing model. Improved balance in route allocation among vehicles and more uniform customer service were also observed. The study revealed that data-driven decisions and computational tools contribute significantly to increasing logistic efficiency. Such gains are particularly relevant for companies operating in regions with limited road infrastructure and a wide dispersion of delivery points, as is the case in the studied microregion.*
Conclusion: *The research demonstrates that the application of routing techniques based on optimization algorithms can generate significant gains in terms of operational efficiency and cost reduction in the regional distribution sector. The findings contribute to the literature by providing empirical evidence in an underexplored Brazilian context and support more rational and sustainable managerial practices. It is suggested that future studies deepen this analysis by expanding the sample, applying it to other logistics segments, and including environmental variables to strengthen integrated decisions between efficiency and sustainability within the regional supply chain.*
Key Word: *Route optimization; Regional logistics; Operational efficiency; Cost reduction; Vehicle routing problem.*

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I. Introduction

In the contemporary global scenario, logistics centers play a strategic role in the efficiency of supply chains, acting as integration points between storage, distribution, and consumption. According to Jesus and Bastos (2024) and Prajapati et al. (2022), when strategically positioned, these centers contribute to cost reduction, improvement of inventory management (by facilitating storage), and greater market responsiveness (through the organization and distribution of goods, thereby ensuring that products reach their destinations quickly and accurately). These factors become even more critical in countries of continental dimensions, such as Brazil, where the predominance of road transportation and inequality in transport infrastructure impose significant challenges to regional logistics (Souza & Schmitt, 2024).

Cui et al. (2023) highlight that the decentralization of the logistics network contributes not only to shorter delivery times but also to increased corporate responsiveness. Recent data indicate that, in 2023, Brazil reached over 23.4 million square meters in logistics warehouse infrastructure, reflecting the expansion and importance of these assets within the national value chain (Souza et al., 2024).

The efficiency of goods distribution is, therefore, directly associated with the ability to optimize transport routes (Zeng, 2022). In this context, the Travelling Salesman Problem (TSP) emerges as both a challenge and one of the classical approaches of combinatorial optimization applied to logistics (Bock et al., 2025). The TSP consists of determining the lowest-cost path for an agent to visit a set of locations exactly once, returning to the point of origin. Thus, through algorithms, it enables the reduction of distances, travel time, and operational costs associated with the total distance traveled (Cui et al., 2023). As also highlighted by Pop et al. (2024), the solutions derived from and the multiple approaches to the TSP directly impact logistic efficiency, cost reduction, and have been continuously adapted to real-world contexts with multiple constraints.

Recent studies reinforce the relevance of applying vehicle routing optimization techniques. For instance, Du et al. (2021) demonstrated the effectiveness of genetic algorithms in solving the TSP within the retail sector, resulting in a significant improvement in delivery performance and efficiency. Such advances, by incorporating computational intelligence into logistics planning, constitute a competitive advantage in increasingly demanding markets regarding speed and service predictability (Leng & Li, 2021; Naganawa et al., 2024).

Beyond business benefits, intelligent transport routing has direct implications for urban public management. Route rationalization contributes to reducing the number of vehicles in circulation and travel time, thereby mitigating potential urban congestion and lowering pollutant gas emissions. This aligns with urban sustainability guidelines and the Sustainable Development Goals (SDGs), particularly Goal 11 (Sustainable cities and communities), Goal 13 (Climate action), and Goal 3 (Good health and well-being) (United Nations, 2015; Souza & Schmitt, 2024).

In this context, cooperation between public and private sectors is crucial for the adoption of more environmentally sustainable and technologically advanced logistics solutions. Public policies that encourage the use of route optimization technologies, combined with investments in logistics infrastructure, amplify economic, social, and environmental gains (Mele et al., 2021; Jesus & Bastos, 2024; Souza et al., 2024). Moreover, according to Prajapati et al. (2022), society's growing awareness of the impacts of logistics strengthens the demand for solutions that prioritize more efficient, sustainable, and community-oriented practices. Thus, informed consumers tend to value companies that adopt sustainable and efficient practices, positively influencing the market (Cordeau et al., 2025). Additionally, the active participation of the community in discussions about urban mobility and logistics contributes to the development of solutions that are better aligned with local needs (Zeng, 2022).

Therefore, logistics centers and transport routing are configured as central elements in building more resilient, economical, and environmentally responsible supply chains (Kijewska et al., 2021). As emphasized by Bock et al. (2025), the adoption of models and solutions based on the TSP, in synergy with institutional cooperation (public and/or private) and active societal participation, represents a promising path toward logistics innovation, urban modernization, and business competitiveness in a global scenario.

In this context, the present study aimed to apply the Travelling Salesman Problem (TSP) to optimize delivery routing from a main logistics center to several regional distribution centers in the state of Espírito Santo. The proposal sought to identify routes that minimized the distance traveled and operational costs while maximizing distribution efficiency. To achieve this, mathematical modeling was employed using optimization algorithms applied to real georeferenced data, considering operational constraints such as vehicle capacity and traffic conditions.

II. Theoretical Foundations

The expansion of Brazilian cities and the growing demand for efficient logistics services pose increasingly complex challenges to urban traffic management and goods distribution. In this context, product routing emerges as an essential strategy to optimize transport flows, reduce operational costs, and improve the quality of services provided (Liu et al., 2022). Among applicable mathematical models, the Travelling Salesman Problem (TSP) stands out, whose versatility makes it suitable for developing effective logistics solutions (Du et al., 2021).

According to Pop et al. (2024), the TSP is a classical problem of combinatorial optimization, aimed at determining the most efficient route for an agent to visit a set of distinct locations exactly once before returning to the point of origin. In logistics applications, this approach allows for reduced travel distances, minimized fuel consumption, and improved delivery time management (Zeng, 2022). However, its applicability transcends the private sector, being equally relevant to public services, such as public transport management, solid waste collection, urban parcel delivery, and urban mobility planning (Mele et al., 2021).

In this regard, Bernal et al. (2021) highlight that the growing complexity of urban centers requires the application of robust mathematical models capable of assisting in the planning of logistics and the distribution of goods and services. The TSP, due to its ability to generate optimal solutions for different contexts, has been widely employed by transport companies, retail networks, and logistics operators to optimize resource use, improve operational flow, reduce waste, enhance operational reliability, and directly benefit both service providers and end consumers (Du et al., 2021; Bock et al., 2025).

Accelerated urban growth, in turn, poses significant challenges to territorial and urban logistics planning, requiring integrated policies that simultaneously consider mobility, the environment, and infrastructure (Rinaldi et al., 2023). According to Kijewska et al. (2021), decentralization through urban logistics hubs, combined with incentives for sustainable transport, can significantly help reduce road saturation and improve the flow of goods distribution. Complementarily, Cordeau et al. (2025) emphasize the importance of cooperation between the public and private sectors in developing urban logistics solutions that are sustainable and aligned with the actual needs of territories.

The advancement of the digital economy has led to a sharp increase in the demand for on-demand deliveries, especially in urban contexts. This phenomenon makes logistics efficiency a competitive differential, driving models such as logistics crowdsourcing and the use of autonomous fleets, which are increasingly being consolidated as viable alternatives to meet modern consumer demands (Deng et al., 2022; Liu et al., 2022). However, as noted by Naganawa et al. (2024), this transformation imposes additional challenges, such as the need for effective real-time operational management and the adoption of strategies that reconcile speed and sustainability.

The pursuit of sustainable urban logistics goes beyond the simple optimization of costs and distances. Mele et al. (2021) argue that sustainability in urban transport involves concrete actions to mitigate negative impacts, such as encouraging the use of electric or low-emission vehicles and prioritizing routes with lower environmental impact. For this to occur, it is essential to integrate logistics planning, public policies, the adoption of innovative technologies, and business strategies (Leng & Li, 2021; Zeng, 2022).

The digitalization of the supply chain plays a central role in optimizing the speed and flexibility of logistics operations in an omnichannel environment (Rinaldi et al., 2023). According to Pop et al. (2024), the use of technologies such as blockchain, artificial intelligence, and machine learning enables real-time monitoring, greater delivery predictability, and route optimization based on dynamic data. This enhanced connectivity between different distribution channels favors operational flexibility and continuous adaptation to market conditions, increasing the resilience of logistics chains and consumer satisfaction (Bernal et al., 2021).

Another significant logistical challenge lies in the inadequacy of urban infrastructure to accommodate the growing volume of freight vehicles (Leng & Li, 2021). Restrictions on circulation during peak hours, prioritization of alternative and less polluting modes such as cargo bikes and urban rail systems, and the creation of decentralized distribution centers have been adopted by major urban centers as ways to mitigate structural bottlenecks (Bernal et al., 2021). Such strategies aim to promote a balance between logistical performance and the mitigation of negative impacts such as congestion, delays, and environmental degradation (Ping et al., 2024).

In this scenario, the digitalization of urban logistics emerges as a determining factor in overcoming sustainability challenges (Mele et al., 2021). The use of big data and artificial intelligence not only enables efficient routing but also optimizes trajectories and dynamically responds to traffic conditions and variable market demands. This integration provides greater predictability and stability to operations, resulting in more resilient supply chains prepared to face seasonality, market fluctuations, and unexpected disruptions (Leng & Li, 2021). Thus, intelligent and sustainable logistics consolidates itself as a strategic element for business competitiveness and responsible urban planning (Deng et al., 2022).

Bock et al. (2025) point out that stricter regulations and new environmental goals have led companies to reassess their logistics strategies, prioritizing solutions that meet legal requirements and reduce environmental impacts. Initiatives such as low-emission zones, tax incentives for the use of electric vehicles, and restrictions on the circulation of fossil-fuel-powered vehicles are reshaping traditional urban transport models. According to Zeng (2022), compliance with these regulations not only ensures regulatory conformity but also improves public perception (corporate reputation) and promotes the adoption of more sustainable practices.

Applied studies on the use of the TSP in delivery routing have shown significant improvements in predictability and reductions in operational costs. Du et al. (2021), for example, found that applying the model to perishable goods chains resulted in optimized routes, faster deliveries, and reduced merchandise waste. Furthermore, the integration of the TSP with technologies such as Geographic Information Systems (GIS) and real-time monitoring further expands the possibilities for dynamic route adjustments, promoting greater efficiency, cost savings, and increased operational reliability (Pop et al., 2024).

From a mathematical perspective, the TSP consists of an optimization problem recognized for its wide range of applications, aiming to determine the shortest possible route that traverses a specific set of locations, returning to the starting point. It is a combinatorial optimization problem that can be formalized, as presented by Lin (1965) and Lin & Kernighan (1973), with more recent updates by Dell'Amico et al. (2021) and Pop et al. (2024), as follows:

$$\min. \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} d_{ij} x_{ij}$$
(1)

Sujeito a:

$$\sum_{i=1, i \neq j}^{n} x_{ij} = 1, \ \forall \ j = 1, \dots, n$$
(2)

$$\sum_{i=1, i \neq j}^{n} x_{ij} = 1, \ \forall \ i = 1, \dots, n$$
(3)

$$u_i - u_j + n x_{ij} \leq n - 1, \ 2 \leq i \neq j \leq n$$
(4)

Where d_{ij} is the distance between location i and location j, x_{ij} is a binary variable equal to 1 if the route goes from location i to location j, and 0 otherwise; and u_i are auxiliary variables to prevent sub-tours or sub-routes.

In logistics centers, which play a central role in load consolidation and redistribution, the application of the TSP enables maximization of fleet productivity, reduction of redundant routes, and improvement in operational predictability (Bernal et al., 2021; Liu et al., 2022). According to Deng et al. (2022), TSP-based modeling represents a strategic solution in supply chains facing operational, logistical, and environmental constraints.

The pursuit of sustainable solutions also drives the application of the TSP in logistics (Rinaldi et al., 2023). For example, reducing the carbon footprint and optimizing resource utilization are essential factors to meet the growing demand for environmentally responsible logistics solutions (Kijewska et al., 2021). In this sense, intelligent routing not only promotes cost reduction but also contributes to the sustainability of cities, organizations, and to an improved quality of life for citizens (Mele et al., 2021).

Finally, Zeng (2022) emphasizes that changes in consumer behavior, with increased appreciation for sustainable practices, are leading companies to invest in green logistics. The growing demand for environmentally responsible deliveries has driven companies to invest in recyclable packaging, electric fleets, and carbon offset initiatives (Bock et al., 2025). This transformation requires logistical planning that considers both operational performance and the environmental and social impacts of each decision (Pop et al., 2024), reinforcing the central role of the TSP as a strategic tool in contemporary logistics, prioritizing efficiency while taking into account its environmental and social impacts.

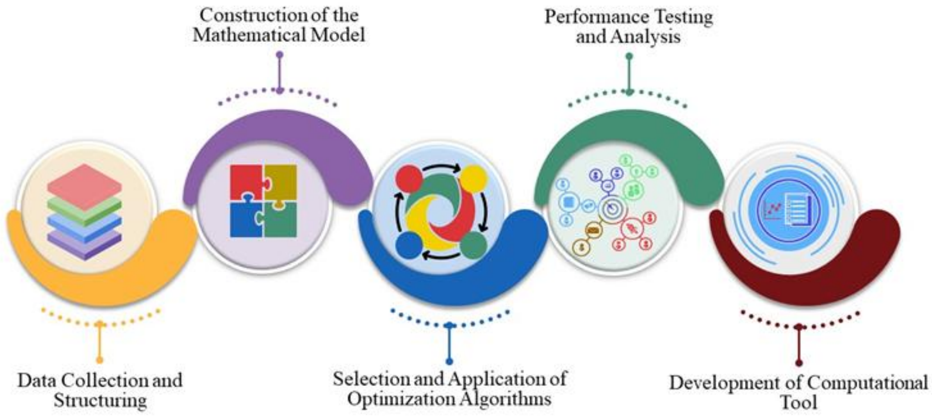
III. Material And Methods

The Travelling Salesman Problem (TSP) was employed as the foundational framework for optimizing delivery route planning from a primary logistics hub responsible for supplying various regional distribution centers. In order to enable both the analysis and implementation of the proposed model, a spreadsheet application was developed to organize geographic data, compute distances between locations, and support the application of optimization algorithms, in accordance with the methodology proposed by Naganawa et al. (2024). This tool facilitated simulations across different logistical scenarios, allowing for the evaluation of route efficiency in terms of operational cost reduction and delivery time optimization. Figure 1 below presents the logical sequence of the five phases that structure the research, from the collection of operational data to the implementation of the routing computational tool based on the Travelling Salesman Problem (TSP).

The first stage involved the collection and systematization of operational data related to the main logistics hub and the regional distribution centers. Based on the framework proposed by Manoharame et al. (2021), the geographical coordinates of each logistics point were mapped, inter-location distances were recorded, and critical variables were identified, such as vehicle capacity, time window constraints, and prevailing road conditions. These data were organized into a structured database using a spreadsheet, thereby providing the foundational basis necessary for the application of modeling and optimization methods (Rinaldi et al., 2023).

The second stage consisted of modeling the logistics network as a directed graph, in which vertices represent delivery points (logistical nodes), and edges symbolize the feasible paths between them, as proposed by Liu et al. (2022). The mathematical formulation aimed to minimize the total distance traveled, ensuring that each point would be visited exactly once, while complying with operational constraints such as load capacity and service time (Leng & Li, 2021). The objective function was based on the aggregated cost per kilometer, integrating practical feasibility constraints into the computational modeling process (Kijewska et al., 2021).

Figure 1 – Stages of the methodological approach adopted for the modeling, simulation, and optimization of logistical routes



Source: Authors (2025).

In the third stage, following the guidelines of Özarık et al. (2024) and Ping et al. (2024), both exact and heuristic approaches based on Integer Linear Programming Methods were employed for small-scale instances, ensuring optimal solutions within acceptable computational limits. For more complex scenarios, characterized by a higher number of delivery points and geographical variability, heuristic and metaheuristic strategies such as Genetic Algorithms, Simulated Annealing, and Ant Colony Optimization were utilized (Pop et al., 2024; Bock et al., 2025). In these more intricate cases, hybrid strategies were also tested to refine results and adapt the model to different territorial configurations (Rinaldi et al., 2023).

In the subsequent stage, the generated solutions were tested across various simulated scenarios, allowing comparison with traditional routing approaches, which are often based on the logistic operator's intuition or simple linear distances between points (Naganawa et al., 2024). The key performance indicators analyzed included: (i) total distance traveled, (ii) reduction in operational costs, (iii) optimization of delivery time, and (iv) efficient fleet utilization. The simulations also considered real-world constraints, such as unpaved roads, urban traffic conditions, and destination accessibility. Additionally, the results were subjected to statistical testing to validate the robustness of the method and ensure its applicability in real operational contexts (Zeng, 2022).

Finally, based on the tested models and algorithms, a computational tool was developed to automate the routing process (Dell'Amico et al., 2021). The application interface enabled the input of new data and dynamic adaptation of routes according to changes in operational conditions, resulting in a flexible system with a user-friendly interface, adaptable to various datasets and applicable across diverse logistical scenarios. Consequently, the automation of the routing process through this tool enabled the practical application of the model in real-world contexts and contributed to enhanced operational decision-making (Deng et al., 2022).

IV. Result And Discussion

Distribution logistics in regions with diverse topography requires robust strategies to ensure efficiency in the flow of goods. In the state of Espírito Santo, which features varied terrain and a road network with differing levels of accessibility, the challenge of connecting heterogeneous urban centers increases the complexity of logistical operations. Accordingly, a hierarchical logistics model was established, originating from a Primary Distribution Center (PDC), located in São Mateus—a strategic municipality in the northern region of the state—responsible for supplying six Central Distribution Points (CDPs), which, in turn, redistribute goods to 29 municipalities within their respective microregions and to their associated Distribution Centers (DCs).

The definition of the logistics hubs was based on geographic location and road network connectivity criteria. São Mateus was selected as the PDC due to its strategic position in northern Espírito Santo, with direct connections to both coastal and inland areas (Figure 2). The CDPs were allocated in the following municipalities: Santa Teresa (Central Serrana), Vila Valério (Central-West), Fundão (Metropolitan), Conceição da Barra (Northeast), Nova Venécia (Northwest), and Sooretama (Rio Doce). This structure, inspired by decentralized logistics networks (Cui et al., 2023), aims to reduce travel time and operational costs while increasing the reach and capillarity of the distribution system.

Figure 2 – Distance matrix between selected regional logistics hubs in Espírito Santo

Central Mountain Region

	1	2	3	4
1		11	43	53
2	11		32	43
3	43	32		28
4	53	43	28	

Caption: (1) Itaguaçu. (2) Itarana. (3) Santa Maria de Jetibá. (4) Santa Tereza.

Northwest Region

	1	2	3	4	5	6
1		75	37	51	102	69
2	75		54	97	69	57
3	37	54		46	67	34
4	51	97	46		82	64
5	102	69	67	82		33
6	69	57	34	64	33	

Caption: (1) Água Doce do Norte. (2) Águia Branca. (3) Barra de São Francisco. (4) Ecoporanga. (5) Nova Venécia. (6) Vila Pavão.

Central-West Region

	1	2	3	4	5	6
1		48	108	72	114	141
2	48		53	26	79	106
3	108	53		31	46	39
4	72	26	31		64	74
5	114	79	46	64		28
6	141	106	39	74	28	

Caption: (1) Baixo Guandu. (2) Colatina. (3) Governador Lindenberg. (4) Marilândia. (5) São Gabriel da Palha. (6) Vila Valério.

Metropolitan Region

	1	2	3
1		62	23
2	62		57
3	23	57	

Caption: (1) Cariacica. (2) Fundão. (3) Vila Velha.

Northeast Region

	1	2	3	4	5	6	7
1		76	116	149	53	71	135
2	76		118	151	90	78	140
3	116	118		33	64	48	22
4	149	151	33		96	81	16
5	53	90	64	96		31	86
6	71	78	48	81	31		67
7	135	140	22	16	86	67	

Caption: (1) Conceição da Barra. (2) Jaguaré. (3) Montanha. (4) Mucurici. (5) Pedro Canário. (6) Pinheiros. (7) Ponto Belo.

Sao Mateus Region

	1	2	3	4	5	6	7
1		38	164	66	191	66	100
2	38		200	100	227	102	136
3	164	200		197	28	192	163
4	66	100	197		185	68	56
5	191	227	28	185		156	168
6	66	102	192	68	156		33
7	100	136	163	56	168	33	

Caption: (1) São Mateus. (2) Conceição da Barra. (3) Fundão. (4) Nova Venécia. (5) Santa Tereza. (6) Sooretama. (7) Vila Valério.

Rio Doce Region

	1	2	3	4	5	6
1		22	33	60	94	107
2	22		28	75	109	122
3	33	28		67	101	114
4	60	75	67		36	48
5	94	109	101	36		31
6	107	122	114	48	31	

Caption: (1) Aracruz. (2) Ibiraçu. (3) João Neiva. (4) Linhares. (5) Rio Bananal. (6) Sooretama.

Source: Authors (2025).

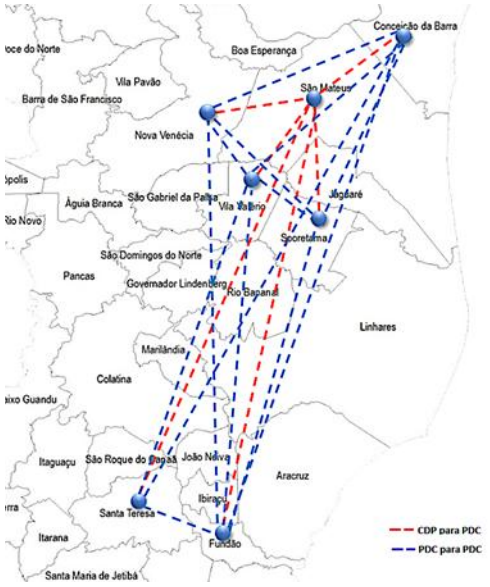
As a starting point, a distance matrix was constructed between the regional hubs using data obtained from Google Maps, with the objective of measuring connectivity and identifying potential critical logistical bottlenecks. This analysis revealed the predominance of routes exceeding 100 km in at least four of the six regions studied, thereby reinforcing the need for an optimized routing model that considers not only linear distances but also variables such as average travel time, road type, and operational constraints.

The analysis of the distance matrix also revealed an asymmetric distribution between the Central Distribution Points (CDPs) and their respective Distribution Centers (DCs), indicating that geographic proximity does not necessarily imply logistical accessibility. In some regions, such as the Northeast and Central Serrana, the road network imposes significant constraints on the fluidity of travel, resulting in longer travel times even for relatively short distances. This finding underscores the importance of incorporating geotechnical and infrastructural variables during the planning phase. Moreover, it highlights the need for continuous route reassessment based on empirical performance data, such as actual delivery times and operational costs.

The simulation of the routing model, based on the optimal solution to the Travelling Salesman Problem, indicated the following minimum-cost route (to determine the most efficient path connecting the Primary Distribution Center to the six CDPs): Conceição da Barra → Fundão → Vila Valério → Nova Venécia → Santa Teresa → Sooretama, returning to São Mateus. This route was determined using real-world data and optimized through the Excel Solver tool, taking into account distance minimization and logistical balancing (Figure 3). The total route length amounted to 863.3 km, representing an efficient path in terms of distance traveled and operational cost reduction, particularly in supply chains operating with limited logistical resources (Rinaldi et al., 2023).

In the second phase of the study, the same optimization procedure was applied to the Central Distribution Points (CDPs) in relation to the regional Distribution Centers (DCs) under their jurisdiction. The results indicate that each region exhibits specific logistical characteristics that directly affect route efficiency. The Central Serrana region, for instance—characterized by rugged (mountainous) terrain and winding roads—requires routes with gentler inclines, even if they are longer in distance. In contrast, the Rio Doce region displayed high uniformity in its routing, with little variation among routes, while the Northeast region exhibited high complexity due to the distances between DCs and the presence of poorly maintained secondary roads.

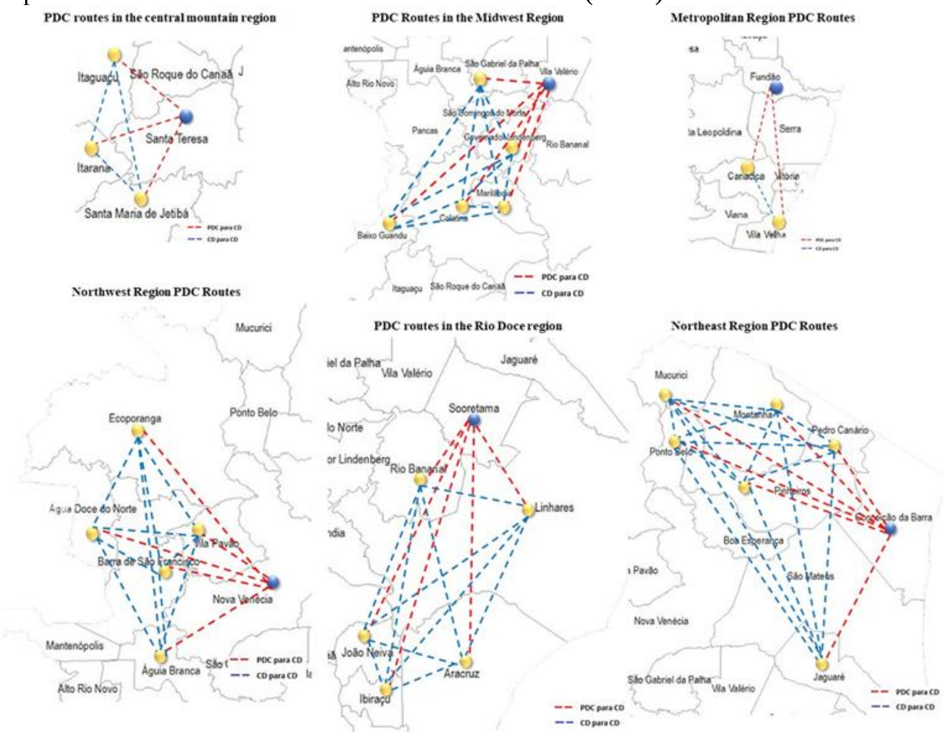
Figure 3 – Optimal distribution route from CDP São Mateus to the six regional distribution points



Source: Authors (2025).

On the other hand, in the Central-West region, the dispersion of DCs necessitated a feasibility analysis with multiple routing alternatives. These findings demonstrate that, although the hierarchical distribution model is replicable, its application requires adaptations that take into account the territorial and logistical particularities of each subregion. These aspects confirm the importance of incorporating geographical variables into the modeling process (Naganawa et al., 2024) (Figure 4).

Figure 4 – Optimized routes between Central Distribution Points (CDPs) and local Distribution Centers (DCs)



Source: Authors (2025).

It was observed that the shortest distance does not always result in the shortest travel time, due to structural road conditions and traffic patterns. For this reason, the analysis incorporated qualitative variables such as the presence of unpaved road segments, historical closures during rainy periods, and seasonal traffic fluctuations—particularly during the wet season. These factors, as discussed by Naganawa et al. (2024), should be considered in logistics models tailored to regions with deficient infrastructure.

In the Metropolitan region (Cariacica and Vila Velha), although comprising only two DCs, intense urban traffic significantly compromises delivery times—a factor also identified by Bock et al. (2025) in a study conducted in the Metropolitan Region of Belo Horizonte. In contrast, the Northeast region, with seven DCs spread across vast areas and connected via secondary roads, showed a substantial increase in cost per kilometer traveled, with fuel representing the largest component of the variable cost (USD 0.24/km) (Table 1).

Table 1 - Composition of logistics costs per kilometer traveled in regional operations

Description (cost per km)	Value (USD)	Cost
Depreciation	0,025	Fixed
Administrative Costs	0,04	
IPVA and Mandatory	0,015	Variables
Insurance	0,005	
Maintenance	0,056	
Salaries	0,03	
Tire Overtime	0,025	
Fuel	0,24	

Source: Authors (2025).

Population density and the concentration of Distribution Centers (DCs) also proved to be critical determinants of logistical performance. In regions with low population density and sparse demand—such as parts of the Northeast—vehicles travel greater distances per delivery, which increases the cost per transported unit. In contrast, in more urbanized regions, the high concentration of deliveries per route offset the challenges posed by traffic congestion. These differences highlight the need for customized regional supply policies that take into account territorial characteristics and local demand. Additionally, the importance of preventive fleet maintenance and delivery window planning is emphasized as a means to mitigate the effects of urban congestion and the long travel distances required in peripheral areas.

In the Northwest and Rio Doce regions, territorial homogeneity and the presence of consolidated logistics infrastructure—as seen in municipalities such as Linhares and Aracruz—enabled the design of optimized routes with less variability between nodes. These conditions enhanced logistics performance by allowing route plans to be adjusted more easily, reducing idle time and improving vehicle load efficiency. The existence of intermediate structures such as freight terminals and service garages strengthened operational flexibility and reduced inefficiencies, supporting the findings of Jesus and Bastos (2024), who emphasize the importance of intermediate urban centers for ensuring the fluidity of logistics routes. Therefore, logistics network planning should, whenever possible, incorporate these structuring nodes.

The analysis of logistics costs (Table 1) identified fuel and labor as accounting for approximately 66% of the total cost per route. The application of optimization models demonstrated a significant reduction in total distance traveled, resulting in notable gains in operational efficiency. These results align with the findings of Souza and Schmitt (2024), who highlight the direct impact of strategic routing on the financial sustainability of logistics chains.

Thus, the present study demonstrated that the use of accessible computational tools—such as electronic spreadsheets—combined with the classical Traveling Salesman Problem (TSP) model, can provide robust and replicable solutions to complex logistics problems in regional contexts. The integration of geographic data, operational variables, detailed cost structures, and optimization algorithms provided a practical and scalable approach applicable to various territorial realities. This contributes both to the advancement of research in logistics and transport planning, and to the formulation of interventions that balance operational efficiency and economic feasibility (Pop et al., 2024).

V. Conclusion

This study investigated the application of the Traveling Salesman Problem (TSP) as a decision-support tool for optimizing product distribution logistics in the state of Espírito Santo, Brazil, focusing on the construction of efficient routes from a main logistics center to various regional hubs. Through mathematical modeling and the use of optimization algorithms implemented in an accessible computational environment (Excel/Solver), it was demonstrated that significant improvements in operational efficiency can be achieved by reducing operational costs and increasing delivery predictability.

The proposed solution, based on real georeferenced data and concrete operational parameters, resulted in an optimal route of 863.3 km, efficiently serving ten Central Distribution Points (CDPs) with minimal route overlap. These findings reinforce the importance of mathematical models and optimization techniques as strategic instruments for decision-making in logistics planning—particularly in competitive business environments and regional contexts characterized by structural challenges and high geographic dispersion. Moreover, the solution facilitates faster and more predictable deliveries, minimizing operational failures and improving customer experience.

The results also revealed substantial resource savings, particularly through reductions in travel time and variable costs, with emphasis on fuel consumption and labor compensation. Additionally, the decentralization of the logistics network via a hierarchical structure contributed to more balanced load distribution, enabling more uniform and economically sustainable deliveries.

However, certain limitations must be acknowledged. The modeling was based on fixed average distances obtained through Google Maps, disregarding dynamic factors such as weather conditions, temporary road restrictions, seasonal demand fluctuations, and unforeseen logistical events. These simplifications may affect the real-world applicability of the results, underscoring the need for more robust models. Furthermore, the use of Solver as the optimization tool restricts the analysis to a specific method, suitable only for small- to medium-scale instances, without fully exploring the potential of advanced heuristics or artificial intelligence.

Therefore, future research is recommended to explore the application of more sophisticated hybrid and metaheuristic methods—such as genetic algorithms, ant colony optimization, and machine learning—allowing comparisons between exact and approximate methods. The incorporation of artificial intelligence and machine learning techniques could further support real-time route adaptation, accounting for operational variations. Additional investigations could also examine the economic impact of logistics optimization across different sectors, offering a broader understanding of the benefits of this approach. It is also advisable to integrate environmental and socioeconomic variables—such as carbon footprint, urban accessibility, and quality-of-life indicators—to align logistics decisions with principles of sustainability and social responsibility.

From a practical perspective, the results of this study provide valuable insights for companies seeking to improve their distribution operations, particularly those operating in peripheral regions or areas with limited logistics infrastructure. The adoption of mathematical models combined with computational tools can become a competitive advantage by enabling faster, more predictable, and lower-cost deliveries. To maximize these benefits, it is essential for public managers to use the findings as a foundation for planning more efficient and sustainable distribution networks and to invest continuously in new technologies, adapting their strategies to evolving market conditions.

In summary, the integration of logistics, technology, and sustainability plays a fundamental role in the pursuit of more modern, resilient, and socially responsible business operations. Optimizing distribution routes not only reduces costs but also promotes energy efficiency and emissions reductions, aligning with the United Nations Sustainable Development Goals (SDGs), particularly SDG 9 (Industry, Innovation and Infrastructure), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action). It is hoped that the insights presented here will inspire new research and practical applications that further advance logistics processes, fostering closer alignment between technological innovation, regional routing strategies, economic rationality, and positive environmental impact.

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