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Optimization model of the primary transport network in the food sector in Colombia

Modelo de optimización de la red de transporte primario en el sector de alimentos en Colombia

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Abstract: Logistics management is essential for organizations to generate competitive advantages, especially in Colombia, where geographical conditions and poor road infrastructure raise land transportation costs. This study proposes a mixed integer nonlinear scheduling model to optimize ground transportation costs in a food company, considering constraints such as regional warehouse demand, vehicle capacity, tray return, and use of outsourced transportation. The results of the model show that an optimal allocation of vehicles not only reduces costs but also generates environmental benefits by reducing the number of trips needed and prioritizing vehicles with a lower carbon footprint. In addition, the model ensures the satisfaction of demand in terms of timeliness, quantity and conservation of products, contributing to the competitiveness of companies and the reduction of the environmental impact of their transport operations.

Keywords: Land logistics, primary transport, mixed integer linear scheduling, optimization model.

Resumen: La gestión logística es fundamental para que las organizaciones generen ventajas competitivas, especialmente en Colombia, donde las condiciones geográficas y la infraestructura vial deficiente elevan los costos de transporte terrestre. Este estudio propone un modelo de programación no lineal entera mixta para optimizar los costos de transporte terrestre en una empresa alimenticia, considerando restricciones como demanda por almacén regional, capacidad de vehículos, retorno de bandejas y uso de transporte tercerizado. Los resultados del modelo evidencian que una asignación óptima de vehículos no solo reduce costos, sino que también genera beneficios ambientales al disminuir el número de viajes necesarios y priorizar vehículos con menor huella de carbono. Además, el modelo asegura la satisfacción de la demanda en términos de oportunidad, cantidad y conservación de los productos, contribuyendo a la competitividad de las empresas y a la reducción del impacto ambiental de sus operaciones de transporte.

Palabras clave: Logística terrestre, transporte primario, programación lineal entera mixta, modelo de optimización.

1. INTRODUCTION

1.1 Background

The trade of goods between countries or between regions of the same country has become a fundamental element in the economy, for this reason, the good management of land freight transport logistics is essential for the generation of competitive advantages that support commercial success both in countries and in companies. Thus, for companies operating in the perishable food products sector in Colombia, it is a permanent concern to optimize transportation costs, considering that the country's complicated logistics infrastructure and high logistics costs negatively impact their profitability and competitiveness [1], [2], [3].

The implementation of strategies that minimize transportation costs in Colombia's food sector is essential considering that the importance of these companies to Colombia's economy is significant considering their high contribution to the country's GDP and employment and that the cost of transportation represents on average 35% of the price of food [4], [5] products. Operations research has generated optimization models applicable to the minimization of transportation costs based on linear scheduling [6], [7].

Recent research has focused on evaluating the use of various mathematical models derived from operations research to optimize efficiency indicators and costs in the logistics of transporting food products. For example, depending on the procedures required for the implementation of the model, the Vogel approximation method was recommended to optimize land freight transport in the food sector. [8].

Optimization models in freight transport have been used to improve the volumetric utilization indicator of vehicles in the food sector, in a case study in Brazil, the implementation of a model of this type allowed to improve both the occupancy rate of vehicles and the sequence of delivery of products. with which it was possible to reduce the number of vehicles used in the logistics operation and significantly increase the company's profits compared to those obtained with empirical decisions [9].

Optimization models have also been implemented from operations research such as those of classic assignment or flow problem in multi-product networks to generate optimal product shipping policies. In a case study in a Colombian food products company, this type of model was implemented to optimize logistics and transportation costs subject to restrictions on demand satisfaction, capacity of both transport vehicles and dispatch centers, and types of packaging. The use of these mathematical models can help companies to analyze and optimize their logistics processes in the primary transport of goods [10].

The mixed integer scheduling model has been successfully implemented to optimize supply logistics between warehouses receiving imported products and a processing center, this model could also be used for daily vehicle scheduling to meet fleet constraints and improve logistics performance indicators such as cost of operation. the number of vehicles and customer satisfaction [11].

The classical model that emerged from operations research for the solution of the transport problem proved an efficient allocation of routes and the optimal selection of transport vehicles to minimize the number of vehicles and the associated costs. This model is based on satisfying the demand of distribution centers based on capacity constraints of some centers of origin with the aim of minimizing the logistics costs of the transport operation. The use of integer linear programming models can improve logistics efficiency in its basic indicators such as costs, capacity, quality and delivery time [12].

Mixed integer linear scheduling models have proven effective in reducing costs and lessening the impact of the logistics network by implementing optimal policies related to routing, vehicle allocation for fueling, and the location of circular coffee shops in Canada. The use of this type of model not only entails economic benefits related to the reduction of costs and the increase in profits, but also contributes to the consolidation of sustainable business models by reducing the carbon footprint in transport operations [13], [14].

A mixed integer scheduling model was implemented in order to reduce logistics costs in a complex fertilizer land transportation network that ranges from import ports to mezcal plants and distribution centers. The results of the implementation of this model showed a reduction in transport costs throughout the logistics network and also managed to reduce greenhouse gas emissions (specifically carbon dioxide) by 23.9% compared to the emissions of the previous method. Optimization models based on linear programming have also proven to be efficient in reducing the environmental impact generated by carbon dioxide emissions in maritime transport [15], [16].

Taking into account this background, this work answers the research question: How to assign the vehicles for transporting perishable food from the central distribution center to warehouses located in important Colombian cities from where the products are distributed to retail customers? For which a multinational that has been operating for more than twenty years in Colombia was taken as a case study.

1.2 Context

The primary distribution logistics network is characterized by a hub-and-spoke distribution system, where the distribution center acts as a central node that coordinates product flows to eleven destination sales centers. The logistics operation of this company uses a standardized system of cargo units called "Dolly", which consists of a tower of stackable baskets where the product is stored and transported. Dollys are crucial elements in the logistics of this company acting as an interface between static storage and dynamic transport.

The primary transport network is managed through alliances with seven transport companies that provide a heterogeneous fleet composed of approximately 50 vehicles of different capacities, including turbo, single, minimule and autotrain units. The company's primary transport operation mobilizes an average of 25 vehicles per day to nine destination cities (see table 1), handling operational restrictions such as fuel availability, return types and load capacities measured in dollies.

The capacity of the vehicles is measured in number of base dollys, with the possibility of mounting between 2 to 5 additional dollys in the vehicles of greater capacity, although this practice is limited by weight restrictions and considerations of preservation of the product (see table 2). The complexity of this logistics network requires detailed analysis to optimize resource allocation and improve operational efficiency.

Freight transport rates in Colombia are regulated by the Efficient Cost Information System for Automotive Freight Transport (SICE-TAC), which provides a standardized cost structure by route and vehicle typology. Each transport company applies an intermediation percentage on this standardized rate and in this way the cost of transportation from the central distribution center to each destination is calculated according to the type of vehicle to be hired for daily operation. This costing scheme allows for the establishment of objective comparative parameters for the optimisation of vehicle allocation and the assessment of the economic impact of operational decisions on the transmission network [17].

Describing the flow of product at the nodes of the transmission network is essential to understand how goods movements between distribution centers and sales centers are managed. In this context, the average daily demand for products should be considered in terms of dollys, which represent the units of load used for the transport of products. The daily demand for dollys in each of the 9 sales centers is variable and depends on factors such as geographical location, the storage capacity of each center and the specific needs of customers in each region.

Additionally, it is important to take into account the different modes of transport of products: some trips are made without return, others with product return and others with empty trays returned, which introduces a reverse logistics component. Reverse logistics involves the recovery of empty trays that need to be transported back to distribution centers for reuse, adding complexity to the process of vehicle assignment and route planning.

This flow of products, which includes both the transport of goods to the sales centers and the return of empty products and trays, must be managed efficiently to optimize the use of the available fleet, minimize transport times and reduce operating costs. The detailed understanding of the daily demand per sales center, together with the particularities of each type of trip (no return, with product return or with empty tray return), allows a more appropriate allocation of vehicles and better route planning, contributing to the overall efficiency of the transport network.

This proposed research seeks to develop an integrated optimization framework that simultaneously addresses outsourced vehicle allocation, fleet management, and cost optimization in a multi-vendor environment. Not only does this approach have the potential to significantly improve the operations of the case study company, but it could also provide valuable inputs and an optimization model applicable to other companies in the sector and to the logistics industry in general that operate with similar transport models.

2. MATERIALS AND METHODS

The problem studied in this research is to assign vehicles for the transport of perishable food products from a distribution center located in the central region of Colombia, to general warehouses located in large cities from where they will be distributed to customer service warehouses, to minimize the cost of transportation and therefore contribute to the generation of value for the shareholders of this multinational.

For the design of the model for the optimization of transport costs and CO2 emissions in this multinational, the proposal by [18], which consists of three stages, was used: 1) data preparation; 2) formulation of the mathematical model and; 3) validation of the results. For the first phase of the methodology, data were collected in order to characterize and diagnose the company's primary transport network, characterize the resources of the process, analyze the distribution network, review the current allocation process and perform the analysis of historical data and verify the validity of the assumptions of a Mixed Integer Linear Programming model.

In general, they were analysed with several data sets: 1) the destinations of the distribution, which are 9 in total; 2) transport provider companies, which in total are 8; 3) types of vehicles available for transport by company; 4) cost of transportation for each company by destination and type of vehicle; 5) CO2 emissions for each type of vehicle; 6) demand for each type of product in each destination city; 7) Vehicle capacity by type and; 8) Fuel type for each type of vehicle.

For the second phase of the methodology, the development of the mathematical optimization model for the management of the primary transport network of this multinational in the food sector considered the national distribution center located in the center of the country as the origin node and 9 warehouses located in the main cities of Colombia as destination nodes. The fundamental objective of the model is to minimize total operating costs, while guaranteeing compliance with demand, respecting vehicle capacity restrictions and considering the particularities of each carrier.

This model responds to the prevailing need to systematize and optimize the process of assigning outsourced vehicles to the different routes, considering the multiple operational, logistical and commercial constraints that characterize the operation. The proposed mathematical formulation is based on the principles of mixed integer linear programming, incorporating decision variables for the assignment of each vehicle to a specific route, as well as continuous variables to represent occupancy, carbon footprint and utilization per carrier.

This analytical approach aims not only to significantly reduce the total cost of transportation thanks to the optimal allocation of vehicles, but also to improve the use of resources, mitigate non-compliance in delivery times and contribute to the reduction of the carbon footprint, elements that currently represent significant operational challenges for any organization in the sector. The components of the mathematical model are explained below.

The i index corresponds to the destinations, as summarized in Table 1.

$$i = \{CO, CA, PE, BM, MS, MN, VI, IB, CU\}$$

***Table 1:** Index i associated with the destinations*

Índex i	Destiny
CO	Coast
AC	Cali
EP	Pereira
BM	Bucaramanga
MS	Medellín – warehouse 1
MN	Medellín – warehouse 2
SAW	Villavicencio
IB	Ibagué
CU	Cúcuta

***Source:** own elaboration*

The j index corresponds to transport providers the name of each company has been reduced to a letter type identifier.

$$j = \{H, T, F, B, L, A, C, FP\}$$

The k-index corresponds to types of vehicles and their capacities presented in Table 2:

$k = \{TB, SC, EX1, EX2, AT1, AT2, TM1D, TM1G, TM2, TM3, TM4D, TM4G\}$

Table 2: *J-index associated with vehicle types and their capacities.*

K-índex	Type of vehicle.	K-index	Type of vehicle.
TB	Turbo capacity 16 dollys	TM1D	Diesel Tractor with a capacity of 40 dollies.
SC	Single capacity 22 dollys	TM1G	Gas Tractor with capacity 40 dollies.
EX1	Single extra capacity 25 dollys.	TM2	Diesel Tractor with capacity 42 dollies.
EX2	Single extra capacity 30 dollys.	TM3	Diesel Tractor with a capacity of 46 dollies.
AT1	Auto train capacity 54 dollys.	TM4D	Diesel Tractor with a capacity of 50 dollies.
AT2	Auto train capacity 60 dollys.	TM4G	Gas Tractor with capacity for 50 dollies.

Source: *own elaboration*

The t-index corresponds to the day of the week on which the transport is scheduled, the indicator corresponds to the initials of each day of the week according to its two initials:

$t = (LU, MA, MI, JU, VIE, SA)$

The decision variables of the model are as follows:

$X(i, j, k, t)$: Vehicle assigned to destination I, from supplier J, type K.
$ASR(i, j, k, t)$: Non-Return Vehicle Assignment
$DR(i, t)$: Dollys to be rearranged for destination i in period t.
$UTI(j, t)$: Utilization of company j in period t
$CT(t)$: Transportation cost in period t
$CTOT$: Total cost of transportation.
$OCU(t)$: Occupancy of vehicles in period t
$DS(i, t)$: Occupancy by destination i in period t

The parameters defined for the model are:

$DEM(i, t)$: Daily demand of destination i
$TA(j)$: Supplier intermediation fee j
$CPR(k)$: Roll-up capacity of the k-type vehicle
$CTR(i, k)$: Transportation cost of destination i, with vehicle type k
$CAP(j, k)$A: Conveyor j vehicles, type k capacity
$DIS(j, k, t)$: Daily availability of vehicles of the transport company j, type k
$BHD(t)$: Special deliveries to Bucaramanga
$NSR(t)$: VRecord of no return for Cali in period t
$CO2(i, k)$: Carbon footprint for destination i with the type k vehicle.

The constraints of the model are related to the following aspects:

The demand restriction presented in (1) ensures that the number of Dollys that must be transported is met, taking into account that some vehicles can be rearranged.

$$\left(\sum_{jk} X(ijkt) * CAP(jk)\right) + DR(it) \geq DEM(it) \quad \forall it \quad (1)$$

Fleet capacity restriction ensures that vehicles that are not available are not assigned, see (2)

$$\textstyle\sum_i X(ijkt) \leq DIS(jk) \qquad \forall jkt \quad (2)$$

The restriction on the assignment of vehicles without return (3), ensures a maximum of 2 vehicles without return that correspond to Medellín, and to Cali only when necessary.

$$\sum_{ijk} \left(ASR(ijkt)\right) = 1 + NSR(t) \quad \forall t \quad (3)$$

Dolly's lift capacity restriction (4) ensures that the lift capacity of the vehicles assigned to each destination is not exceeded.

$$\sum_{jk} X(ijkt) * CPRk \geq DR(i, t) \quad \forall it (4)$$

The restriction of maximum Dolly to Ride (5), ensures a maximum of 24 Dollys to Ride per day, in accordance with the company's standards.

$$\sum_{i} DR(it) \leq 24 \quad \forall t \quad (5)$$

The restriction of maximum Dollys to be lifted by city (6), ensures a maximum of 6 Dollys (one vehicle) to be lifted by destination, in accordance with the company's personnel restrictions, excluding Medellín (i=5).

$$DR(it) \leq 6 \qquad \forall i \neq 5 \ , \forall t \qquad (6)$$

The restriction of maximum Dollys to be lifted for Medellín (7), ensures a maximum of 12 Dollys (two vehicles) to be lifted for Medellín, taking into account the consolidated demand of its sales centers.

$$DR("MN", t) \leq 12 \qquad \forall t \quad (7)$$

The restriction on the assignment of one-way carriers for Medellín (8) ensures that at least one vehicle is assigned to the companies that provide one-way service for Medellín, since the company requires that one vehicle per day supply Dollys to the production plant of this center.

$$X(\text{MN,B,TM4D},t) + X(\text{MN,L,TM4D},t) \geq 1 \ \ \forall t \ (8)$$

The restriction on the assignment of a one-way vehicle for Medellín (9), This restriction ensures that a one-way vehicle is assigned to this center.

$$ASR(\text{MN,B,TM4D},t) + ASR("MN","L","TM4D",t) = 1 \ \forall t \ (9)$$

The restriction on the assignment of one-way carriers for Cali (10) ensures that at least one vehicle is assigned from the companies that provide one-way service for Cali.

$$X(\text{CA,C,AT1},t) + X(\text{CA,C,AT2},t) + X(\text{CA,T,TM4D},t) + X(\text{CA,B,TM4D},t) \geq 1 \quad \forall t \ (10)$$

The restriction on the assignment of a non-return vehicle for Cali (11), ensures that a non-return vehicle is assigned for Cali.

$$ASR(\text{CA,C,AT1},t) + ASR(\text{CA,C,AT2},t) + ASR(\text{CA,T,TM4D},t) + ASR(\text{CA,B,TM4D},t) = NSR(t) \quad \forall t \ (11)$$

The assigned vehicle restriction (12) ensures that a vehicle that has not been assigned is not defined without return.

$$ASR(ijkt) \leq X(I,J,K,T) \qquad \forall ijkt \quad (12)$$

The restriction on the allocation of natural gas vehicles for Cúcuta ensures that a gas vehicle is not assigned to this center because it is not possible to supply fuel for the vehicle.

$$\sum_J X("CU",j,"TM1G",t) + X("CU",j,"TM3",t) + X("CU",j,"TM46",t)) = 0 \qquad \forall jt \quad (13)$$

The Bucaramanga special shipping restriction (14) ensures that when there is a special order for Bucaramanga, at least one vehicle from company H is assigned, since they are in charge of making this type of delivery.

$$\sum_k \text{X("BM","H",k,t)} \geq BHD(t) \quad (14)$$

The priority restriction of supplier C (15) ensures that when a Zorro-type vehicle is available, it is prioritized, since these vehicles optimize transportation, but are only contracted for Cali.

$$X(\text{CA,C},k,t) = DIS(\text{C},t,k) \qquad \forall kt \ \ (15)$$

The restriction on the assignment of its own fleet to Ibagué (16) ensures that a vehicle from its own fleet is assigned daily to this destination, since 2 tons of its own fleet are available daily.

$$X(\text{IB,FP,TM4D},t) = 1 \qquad \forall t \ \ (16)$$

The restriction on the assignment of its own fleet to Villavicencio (17) ensures that a vehicle with its own fleet is assigned daily for this destination, since 2 tons of its own fleet are available daily.

$$X(\text{VI,FP,TM4D},t) = 1 \qquad \forall t \ \ (17)$$

Constraints (18) and (19) correspond to non-negativity of the decision variables.

$$X(ijkt) \geq 0 \qquad \forall ijkt \quad (18)$$
$$ASR(ijkt) \geq 0 \qquad \forall ijkt \quad (19)$$

The third phase of the methodology related to the interpretation and validation of the results of the model is presented in the next section of this article.

3. RESULTS

To verify the efficiency of the mixed-integer nonlinear programming model to minimize the total cost of the allocation of perishable food transport vehicles in this firm, the total cost results obtained with the model and the actual costs for each of the days of a specific month were compared. The results of the comparison are presented in Figure 1.

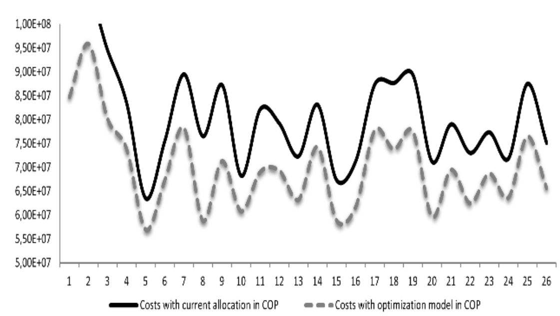

***Fig. 1**. Comparison of total vehicle allocation costs.*
***Source:** Authors.*

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As shown in Figure 1, the total cost of allocating vehicles for each of the days of the month was lower compared to the total cost of allocating with the method used by this multinational food company. In general, the lowest daily savings percentage was 10% and the highest was 23%, the average savings decrease percentage was 13% for the total cost of vehicle allocation in that month.

With the allocation of vehicles resulting from the implementation of the optimization model, the carbon footprint of the operation also decreases in terms of daily CO2 emission in kilograms. The calculation of these emissions was made by applying the standardized methodology of the IPCC-2006. Figure 2 shows the daily comparison for a period of one month of the kilograms of CO2 emission originated by the current allocation of vehicles and those emitted with the allocation generated by the optimization model. The day that the CO2 emission was reduced the least with the optimal allocation was 1% and the maximum decrease was 20%, for the month analysed the average decrease in the carbon footprint was 9%. These results of the proposed model favor global policies related to the reduction of the environmental impact generated by the operation of transport. The optimal vehicle allocation strategy generated by the model prioritizes transportation that uses compressed natural gas as fuel, generating environmental benefits [19].

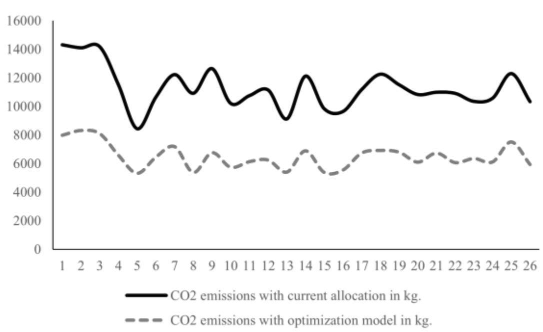

***Fig. 2**. Comparison of the carbon footprint generated by the transport operation.*
***Source:** own elaboration*

The mathematical optimization model for vehicle allocation also proved to improve vehicle occupancy during the period analysed. The indicator increased by 4.2% compared to the reference method used by the company. This increase, while seemingly modest, represents a significant improvement in terms of operational efficiency due to a decrease in the number of trips needed to meet demand. This result has positive implications not only in logistics costs but also in environmental costs by reducing the carbon footprint of the transport operation.

The mathematical model developed allowed a more efficient redistribution of the fleet, increasing the use of conveyors without intermediation and reducing dependence on those with high levels of intermediation. This translates into cost optimization and an improvement in the operational stability of the company's primary transportation system.

Finally, the proposed optimization model recommends maintaining a constant lift of 24 dollys per day, which maximizes the utilization of the vertical capacity available in the highest vehicles. This shows a substantial opportunity for improvement in the operational efficiency of the distribution center. The volatility in the dolly lift indicator with the current schedule suggests the absence of a systematic lift policy, resulting in an underutilization of the vertical space available in the vehicles.

4. CONCLUSIONS

The results of this research showed that mixed integer scheduling models can be considered in companies in the food sector to minimize the transportation costs of distributing their products. In this case, the average savings for the month of evaluation was 13%, which will positively impact the company's operating profits.

This model considered frequent restrictions in this type of companies such as a national distribution center with limited dispatch capacity, regional warehouses with variable daily demand per product, limitations on destinations by transport providers, variable rates by suppliers, requirement of trips with return to the distribution center in some destinations, transport capacity according to various types of vehicles, limitation in destination nodes according to the fuel of the vehicles and limitations of destinations for own vehicles. These elements of the model facilitate generalization to companies with similar characteristics in their distribution logistics network.

The results of the model showed, in addition to the economic benefits for the company, environmental benefits by reducing the negative impact of the distribution operation. These environmental benefits are reflected in the reduction of greenhouse gas emissions, specifically carbon dioxide, in the ground transportation of distribution from the distribution center to regional warehouses. In this case, with the allocation of vehicles generated by the optimization model, the carbon footprint decreased by 13% for the month of analysis. This decrease in the carbon footprint is because the optimal allocation model projects fewer trips to meet the demand of regional warehouses and also prioritizes the use of vehicles that use environmentally friendly fuel. In addition, the results of the model favor the vehicle capacity utilization indicator, which increased by 4.4% compared to the current allocation method.

The implementation of this optimization model for vehicle allocation has resulted in a significant operational improvement of the primary transportation network for this company. The economic, operational and environmental benefits achieved demonstrate the effectiveness of applying a data-driven approach and mathematical optimization to logistics management. These improvements have not only led to cost reduction and greater operational efficiency but can also contribute to better environmental sustainability in the logistics network and increased customer satisfaction in this food sales sector.

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