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Enhancing urban E-commerce efficiency: a fleet composition benchmark

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Received: February 24th, 2025. Received in revised form: June 10th, 2025. Accepted: June 18th, 2025.

Abstract
In Colombia's competitive e-commerce market, accurately estimating last-mile delivery fleets is essential for reducing operational costs. The absence of comprehensive models with operational constraints leads to inefficient resource use and limits sustainable practices. This study proposes a heterogeneous fleet composition model to reduce costs and integrate electric and low-consumption vehicles. The methodology includes a literature review, operational characterization of the target company, and an optimization model for a tactical planning period. A Monte Carlo simulation evaluates demand uncertainty through various scenarios. Results indicate a 9.92% cost reduction and over 200% increase in electric vehicle usage within the fleet, supporting environmental goals. The proposed model offers a decision-making benchmark for Colombian e-commerce companies, enhancing competitiveness and contributing to reduced urban pollution.

Keywords: last-mile; heterogeneous fleet composition; E-commerce, low-emission vehicles; Monte Carlo simulation

Mejorando la eficiencia del comercio electrónico urbano: una referencia para la composición de flotas

Resumen
En el competitivo mercado colombiano de comercio electrónico, estimar con precisión las flotas para la logística de última milla es clave para reducir los costos operativos. La falta de modelos integrales con restricciones operativas genera un uso ineficiente de recursos y limita prácticas sostenibles. Este estudio propone un modelo de composición de flota heterogénea orientado a disminuir costos e incorporar vehículos eléctricos y de bajo consumo. La metodología incluye una revisión bibliográfica, la caracterización operativa de la empresa objetivo y la formulación de un modelo de optimización para un periodo táctico de planificación. Mediante simulación Monte Carlo se evalúa la incertidumbre de la demanda en distintos escenarios. Los resultados muestran una reducción del 9,92 % en los costos y un aumento superior al 200 % en el uso de vehículos eléctricos, posicionando el modelo como una referencia para la toma de decisiones en empresas de comercio electrónico en Colombia, con beneficios económicos y ambientales.

Palabras clave: última milla; composición heterogénea de flota; comercio electrónico; vehículos de bajas emisiones; simulación Monte Carlo.

1 Introduction

E-commerce in Latin America has experienced significant growth, with a projected 25.6% increase in 2023, reaching 5.5% of total retail sales [1]. The COVID-19 pandemic accelerated this trend, introducing millions of new users to online shopping [2]. However, last-mile logistics in urban areas face challenges such as environmental regulations, traffic congestion, and insufficient infrastructure [3]. Major players like Mercado Libre, Rappi, Amazon, and Shopee are reshaping logistics to address these issues and meet regulatory demands [1,2].

How to cite: Peña-Acosta, M., Roldán-Nariño, R.F., and Rincón-García, N., Enhancing urban E-commerce efficiency: a fleet composition benchmark. DYNA, (92)238, pp. 19-25, July - September, 2025.

Last-mile logistics play a strategic role in operating costs and consumer perception. Despite its importance, fleet estimation is often performed empirically or using manual tools. While extensive research exists on the Vehicle Routing Problem (VRP), studies on strategic fleet composition remain limited [4].

A heterogeneous fleet composition model is proposed to optimize last-mile logistics by integrating real operational constraints. The model incorporates electric vehicles and alternative distribution methods to reduce costs and enhance efficiency within a tactical timeframe. It defines fleet requirements based on operational performance, vehicle capacity, and origin-destination matrices. Using insights from literature and service center-specific constraints, the model ensures cost savings, meets sales-driven capacity needs, and implements sustainable transport solutions.

The proposed model undergoes performance evaluation by incorporating stochastic demand behavior, defining an acceptable error margin, and estimating confidence intervals. The results are compared against existing costs, assessing potential improvements and replication feasibility in other last-mile operations to strengthen Colombia's logistics sector.

2 Literature review

The rapid expansion of e-commerce has transformed customer expectations regarding delivery speed, traceability, customization, and location flexibility [5]. However, the concentration of deliveries in urban areas presents significant environmental, regulatory, and logistical challenges [6]. Consequently, last-mile logistics have evolved to integrate sustainability, customer-centric strategies, and cost-efficiency [7].

Last-mile delivery, accounting for up to 50% of total supply chain costs, is critical for customer satisfaction but faces challenges such as demand uncertainty and seasonal variations [7]. Mathematical programming models have been employed to optimize demand management in this context [8,9]. Furthermore, integrating production and distribution remains a complex issue due to fluctuating demand and logistical constraints, addressed through routing optimization algorithms [10,11].

Urban delivery operations are influenced by traffic regulations, congestion, and access restrictions. Load consolidation models have been proposed to improve efficiency [12], while the impact of e-commerce on transport policies has been analyzed through consumer surveys [13]. Fleet composition further complicates last-mile logistics, as heterogeneous fleets introduce additional constraints related to cost, route length, work shifts, and environmental impact [4,14-16].

Fleet optimization methodologies encompass mathematical programming for demand-based vehicle allocation [17-20], heuristic and metaheuristic approaches for solving complex routing problems [21-26], and machine learning techniques for demand forecasting [27,28]. Stochastic variables are frequently integrated into heterogeneous fleet models to address demand uncertainty, employing dynamic programming [21], two-stage optimization frameworks [17,29], and decision tree-based fleet analysis [20].

Research on stochastic vehicle routing predominantly relies on exact methods (51%), followed by metaheuristics (32%) [30]. Multi-stage stochastic optimization has been applied using Sample Average Approximation (SAA) [31], while Monte Carlo simulations have demonstrated effectiveness in fleet cost evaluation [29]. These methodologies contribute to the ongoing development of robust and efficient fleet composition models for last-mile logistics.

3 Problem statement

The case study examines a Colombian e-commerce company operating twelve service centers in major cities and surrounding areas. These centers function as cross-docking platforms, dispatching parcels without storage. Parcel destinations are typically confirmed six hours before departure, requiring volume estimates for fleet planning, with tactical projections set four months in advance and strategic projections one year ahead. The vehicle fleet consists of logistics provider alliances (small vans, electric motorcycles, conventional motorcycles, and electric vans) and owned vehicles, all subject to geographic and security constraints, as detailed in Table 1.

Currently, vehicle allocation is performed manually, with monthly calculations and updates 24 hours before departure, disregarding package volume and specific destinations. This results in inefficiencies, including a 9.44% reserve fleet requirement and an additional 1.95% fleet allocation due to routing mismatches and oversized packages. In total, 11.39% of the chartered fleet is used to compensate for these inefficiencies.

Table 1.
Types of vehicles that can be used.

Vehicle Type	Geography	Security	Autonomy	Package Size
Small Van	All	No zone restriction, can carry an assistant	Unlimited	All
Company-Branded Small Van	All	Zone restrictions due to theft risk, can carry an assistant	Unlimited	All
Auto Rickshaw	Flat	Zone restrictions, cannot carry an assistant	Limited to 60 km	Volume restricted
Motorcycles	All	No zone restriction, cannot carry an assistant	Unlimited	Volume restricted
Electric Van	All	Zone restrictions due to theft risk, can carry an assistant	Limited to 80 km	All
Crowdsourcing	All	No zone restriction, cannot carry an assistant	Limited to 40 km	Volume restricted
Delivery Cell	All	Zone restrictions, cannot carry an assistant	Limited to 5 km	Volume restricted

Source: Created by the authors

Table 2.
Operational characterization.

	Service center	Areas to be served	Type of product	Type of vehicle	Operational period
	12 service centers	148 nodes	3 typologies	9 typologies	6 days
Characterization		Areas to be served from each service center	- Demand	- Cost per vehicle - Capacity limits - Type of contract (own / rented)	- Forecast performance evaluation

Source: Created by the authors

Given Colombia's competitive e-commerce landscape, optimizing last-mile delivery costs is essential. A more efficient approach would enhance fleet utilization by incorporating electric and low-consumption vehicles while considering geographic and volumetric constraints. This strategy would not only reduce operational costs and fleet procurement expenses but also minimize emissions and urban traffic congestion. The research proposes a heterogeneous fleet composition model that integrates sustainable transport solutions to optimize operational efficiency. The key vehicle allocation parameters and constraints are summarized in Table 1.

4 Data analysis

A structured framework for fleet composition modeling is proposed, based on a comprehensive bibliographic review. The framework characterizes operational logistics by defining a distribution network through destination nodes and clustering final customers according to geographic and cost-related factors.

Volumetric package characterization is conducted using a 12-month historical sales analysis, segmenting products into small, medium, and large categories. This segmentation aligns with vehicle load capacities, restricting large packages to high-capacity vehicles. Historical parcel data informs projected volumes per destination, facilitating the construction of an estimation matrix.

Fleet operations are characterized by evaluating loading and travel times, work shifts, delivery durations, capacity constraints, and route dispersion limits over a 12-month period. Additionally, an origin-destination tariff matrix is developed to determine vehicle operating costs, incorporating surcharges for remote deliveries. A summary of these key elements is presented in Table 2.

Finally, a sales forecast analysis compares actual versus estimated performance, assessing error margins by service center and target population. This analysis, fundamental for the stochastic evaluation of the model, will be presented in a subsequent section.

5 Deterministic fleet composition model

We will first take models developed by [17,18] Next, the formulation of a proposal for a mixed integer linear programming mathematical model is detailed, taking the data in the previous chapter as the source for an evaluation period of a typical week. The percentage share of demand for each destination node is taken as fixed for the model, and a maximum limit of packages is defined for each type of vehicle. Regarding this model, volumetric capacity restrictions associated with the characteristics of the packages are defined to each area.

Model notation

Definition of the sets precedes the presentation of the parameters and decision variables, as shown in Tables 3 to 5. The section concludes with the mathematical model that integrates these components into a coherent and structured formulation

Table 3.
Model sets.

Notation	Description
I	Areas to be served
K	Types of vehicle to rent
M	Types of vehicle to own
T	Operation day

Source: Created by the authors

Table 4.
Model parameters.

Notation	Name
D_{it}	Demanded delivery in area I in day t
$RCAP_k$	Capacity of rented vehicle type k
$OCAP_m$	Capacity of owned vehicle type m
CR_{kt}	Cost of operating rented vehicle type k per day
CO_m	Cost of owned vehicle type m in planning period
RE_{ik}	1: If area i can be served with rented vehicle type k, 0: otherwise
OE_{im}	1: If area i can be served with owned vehicle type m, 0: otherwise

Source: Created by the authors

Table 5.
Model variables.

Notation	Name
RV_{kt}	Number of rented vehicles of type k to rent in day t
OV_m	Number of vehicles of type m to be owned
RVD_{kit}	Number of rented vehicles of type k to serve zone i in day t
OVD_{mit}	Number of owned vehicles of type m to serve zone i in day t

Source: Created by the authors

6 Objective function

The objective function minimizes the total vehicle operating cost in period intervals, there are two sets of type of vehicles i) Rented Vehicles and ii) Owned Vehicles. This implies that the number of rented vehicles may vary each day, whereas the number of owned vehicles remains fixed throughout the entire time horizon (1).

$$\min Z = \sum_{k}^{K}\sum_{t}^{T} CR_{kt}\cdot RV_{kt} + \sum_{m}^{M} CO_m OV_m$$

Restrictions

The following is a list of the restrictions contemplated in the model:

$$\sum_{i}^{I} RVD_{kit} \leq RV_{kt} \qquad \forall k \in K, t \in T \tag{2}$$

$$\sum_{i}^{I} OVD_{mit} \leq OV_m \qquad \forall m \in M, t \in T \tag{3}$$

$$\sum_{k}^{K} RCAP_k \cdot RVD_{kit} + \sum_{m}^{M} OCAP_m \cdot OVD_{mit} \geq D_{it} \qquad \forall i \in I, t \in T \tag{4}$$

$$\frac{D_{it}}{\sum_{k}^{K} RVD_{kit} + \sum_{m}^{M} OVD_{mit}} \leq 48 \qquad \forall i \in I, t \in T \tag{5}$$

$$RCAP_k \cdot RVD_{kit} \leq RE_{ki} \cdot D_{it} \qquad \forall i \in I, t \in T, \forall k \in K \tag{6}$$

$$OCAP_m \cdot OVD_{mit} \leq OE_{im} \cdot D_{it} \qquad \forall i \in I, t \in T, \forall m \in M \tag{7}$$

Eq. (2) constrains that the number of rented vehicles sent to each area in each day cannot be greater than the total vehicles to rent in each day. Eq. (3) constrains that the number of owned vehicles sent to each area in each day cannot be greater than the total vehicles to own. Eq. (4) ensures that the demand of each area is satisfied according to the capacity and number of vehicles sent to that area in that day. Eq. (5) ensures that in average vehicle are not planned with more than 48 deliveries to satisfy a working day (10 min per delivery). Eq. (6) ensures that vehicles are not send to areas that cannot be served with that type of rented vehicle, Eq. (7) ensures that vehicles are not send to areas that cannot be served with that type of owned vehicle.

The model is implemented using the open-source optimization package Pyomo in Python. Pyomo is selected for its compatibility with mathematical notation, ease of defining constraints, and integration with data handling (Pandas), graphing (matplotlib), and stochastic modeling (pysp). It supports multiple solvers, including AMPL, CBC, CPLEX, Gurobi, and GLPK, offering flexibility in both commercial and freeware environments.

under stochastic demand conditions.

$$Q(\varepsilon) = \mathrm{E}\left[\min Z = \sum_{k}^{K}\sum_{t}^{T} CR_{kt}\cdot RV_{kt} + \sum_{m}^{M} CO_m OV_m\right] \tag{8}$$

$$(\,\varepsilon) = \frac{1}{N}\sum_{\varepsilon=1}^{N}[Q(\varepsilon)] \tag{9}$$

The proposed model presents certain limitations derived from its own structural assumptions. First, by assuming that the number of owned vehicles remains fixed throughout the entire planning horizon, operational flexibility is constrained in the face of demand fluctuations or unforeseen events. Although the model allows for daily variability in the number of rented vehicles, this is bounded by a maximum daily limit, which may lead to bottlenecks in areas with high demand. Additionally, the model does not account for costs associated with vehicle underutilization or penalties for unmet demand. The constraint of a maximum of 48 deliveries per day, based on an average of 10 minutes per delivery, overlooks potential variations in traffic conditions, service times, and the geographical dispersion of delivery points. Finally, while the restrictions on vehicle accessibility by type are necessary, they may limit service coverage without offering alternative mechanisms to address these areas, potentially compromising overall system efficiency in more complex real-world scenarios.

7 Monte Carlo simulation

After defining the deterministic model, the stochastic behavior of demand is integrated into the fleet composition model. A historical analysis of forecast accuracy over the past 15 months is conducted, evaluating normal, logistic, exponential, gamma, and beta distributions using sum of squared errors (SSE), p-value, and Akaike's Information Criterion (AIC) (Table 6). The logistic distribution is identified as the best fit due to its lowest AIC value.

Based on the forecast analysis, a set of stochastic demand parameters (ε) is generated to estimate operating costs. Using Sample Average Approximation (SAA), the expected cost function (Eq. 8) is reformulated (Eq. 9) under a logistic distribution. The required sample size (N) for a 95% confidence level is determined as 80 (Eq. 10), considering idle vehicle costs. Monte Carlo simulation is then applied to compute confidence intervals (Eq. 11) and estimate the expected error (Eq. 12), ensuring robust fleet composition modeling

$$N = \left(\frac{Z_{95\%} \times \sigma}{ME}\right)^2 = 80.4 \approx 80 \tag{10}$$

$$\bar{X} \mp Z_{95\%} \times \frac{\sigma}{\sqrt[2]{N}} \tag{11}$$

$$Error = \frac{Sup.interval - Inf.interval}{2} \tag{12}$$

Table 6.
Input analysis results.

*Created by the authors*Criteria	Normal	Logistic	Exponential	Gamma	Beta
SSE	0.0726	0.0363	0.4161	0.0761	0.0739
AIC	1.3768	0.6854	3.1232	3.4249	5.3943
P-Value	0.0358	0.6876	0.0020	0.0239	0.0311

Source: Created by the authors

Table 7.
Fleet composition model scenarios.
Source: Created by the authors

	Current Scenario	Deterministic Results	Mean	Inferior Interval	Superior Interval
Total cost (M COP)	$436,400	$397,000	$395,700	$394,600	$396,900
Demand	151.140	151.140	151.401	149.697	152.049
Vehicles	2.415	2.454	2.438	2.432	2.418
Cost per package	$2,888	$2,627	$2,614	$2,636	$2,611
Cost per vehicle	$180,717	$161,800	$162,335	$162,260	$164,155
Saving vs actual Cost per Vehicle	0.000%	11.690%	11.320%	11.370%	10.090%

Source: Created by the authors

8 Results

The company's operations were analyzed through an origin-destination matrix, defining routes by distance, geographic restrictions, and service cost. A 12-month sales analysis identified package volume profiles per destination, and historical demand share was assessed. Vehicle typologies were characterized based on key operational parameters, including load and travel time, work shifts, and volumetric constraints. A tariff matrix with surcharges for remote areas was also developed.

The deterministic fleet composition model optimized vehicle allocation, identifying cost-efficient distribution methods. Execution time was 3.4 minutes on an Intel Core i5-337U with 4GB RAM. The model prioritized vehicles with lower costs per package while considering volume constraints, leading to 9.92% operational savings, reaching up to 28.6% in specific service centers. Savings varied across locations, and compliance with demand restrictions, work shifts, and geographic distribution was validated. Fig. 1 compares the current and proposed fleet compositions.

A Monte Carlo simulation with 80 demand scenarios assessed model robustness, requiring 58.1 minutes for execution. Cost per vehicle savings of 11.69% were observed in the deterministic model, with a stochastic savings estimate of 11.32% at a 95% confidence level, even in worst-case scenarios yielding a 10.09% cost reduction. The model error was $1,155,621 (0.29% of total costs). Table 7 presents cost and demand variations, showing reduced inefficiencies.

Electric vehicle use increased by 277%, from 20 to 86 units per week, while motorcycle-type vehicles decreased from 24 to 14 units. Low-emission motorcycles increased by 57%, reducing costs and CO_2 emissions. The standard deviation in fleet size was 87 weekly units, with daily variations of 3.6%. Compared to the current 11.39% inefficiency, this represents a potential 7.79% fleet reduction. Even in outlier scenarios, savings of 6.76% were achieved despite a 2.56% demand increase. Fig. 2 details the fleet composition adjustments.

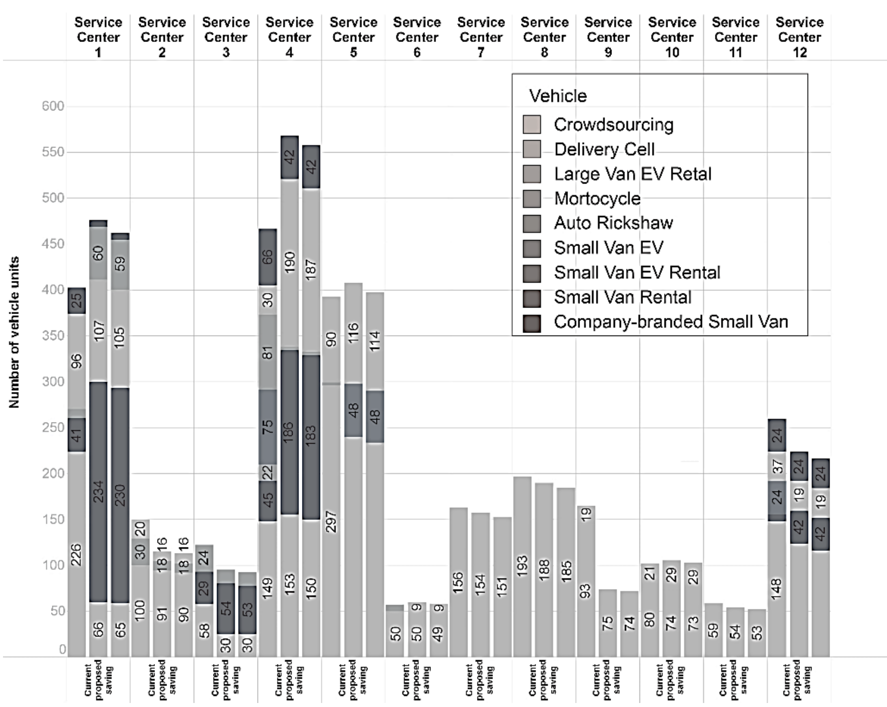

Figure 1. Linear programming model execution results.
Source: Created by the authors

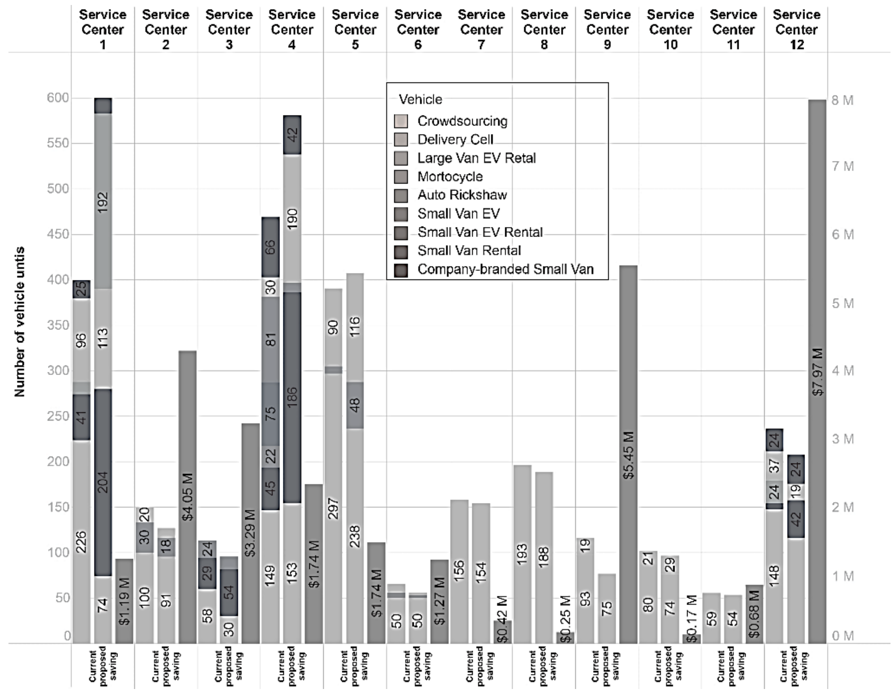

Figure 2. Results comparison.
Source: Created by the authors

9 Conclusions and future research

The objective was to propose a heterogeneous fleet composition model to determine the fleet required to reduce operating costs in last-mile logistics for an e-commerce company in Colombia. This goal was achieved by incorporating key operational constraints and demonstrating an expected cost reduction of 9.92% under a deterministic model. Additionally, the integration of stochastic demand behavior led to an expected savings of 10.27% under uncertainty conditions. This result highlights the relevance of combining deterministic models with stochastic components to better reflect and predict real-world dynamics.

Practically, the model offers companies a structured approach to defining fleet size and type, facilitating informed decisions that align with both cost-efficiency and operational feasibility. The proposed methodology supports replication in similar last-mile logistics contexts and enables the creation of a tailored fleet strategy based on actual operational characteristics. For decision-makers, this provides a robust analytical tool to evaluate trade-offs, anticipate variability in demand, and justify investments in diverse vehicle types, including electric or low-emission alternatives.

Furthermore, the development of a comprehensive reference framework for heterogeneous fleet composition—based on key research trends and solution methods—provides a valuable resource for practitioners seeking to optimize logistics operations. The application of Monte Carlo simulation enhances the model's utility by offering confidence intervals for scenario-based planning, thereby strengthening its use in real-world strategic decision-making. Future work may incorporate two-stage stochastic programming to further enhance the probabilistic robustness of the model.

Funding

This research did not receive additional funding beyond an academic investigation within the university

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